

SemMemDB

Contextualized Semantic Memory using Spreading Activation

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Review of Semantic Memory

Fact-based long term memory store

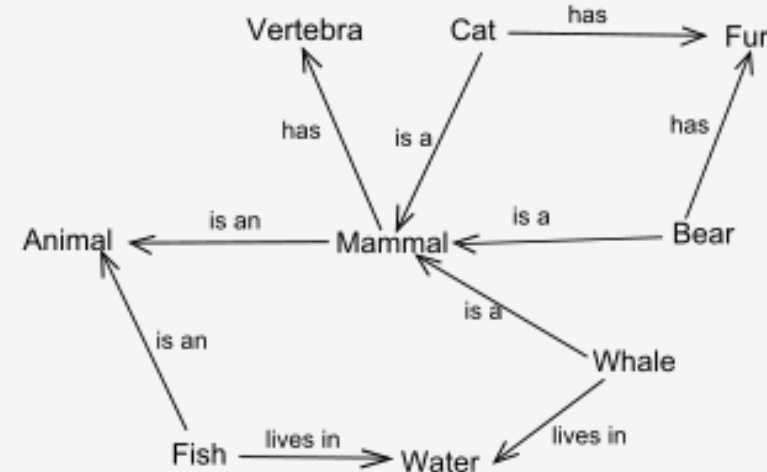
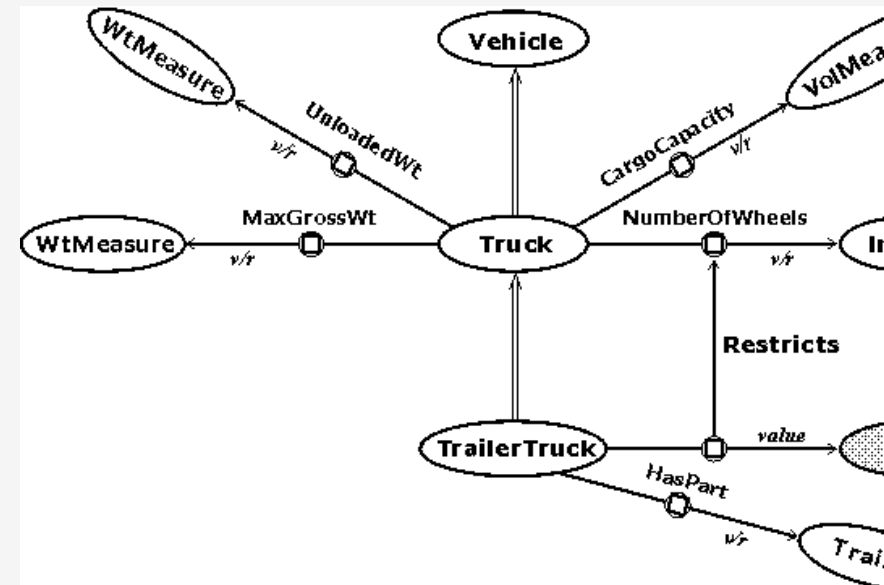
- Songs by a certain artist
- How many wheels a common car has

Memory elements stored in a digraph structure

Inserted data is placed in graph structure based on relations as execution continues

Retrieval occurs as either a direct lookup or query-based retrieval

- Query-based retrieval can lead to some issues with both efficiency and accuracy (ambiguity).



Review of Spreading Activation

allows context to affect SMEM retrieval

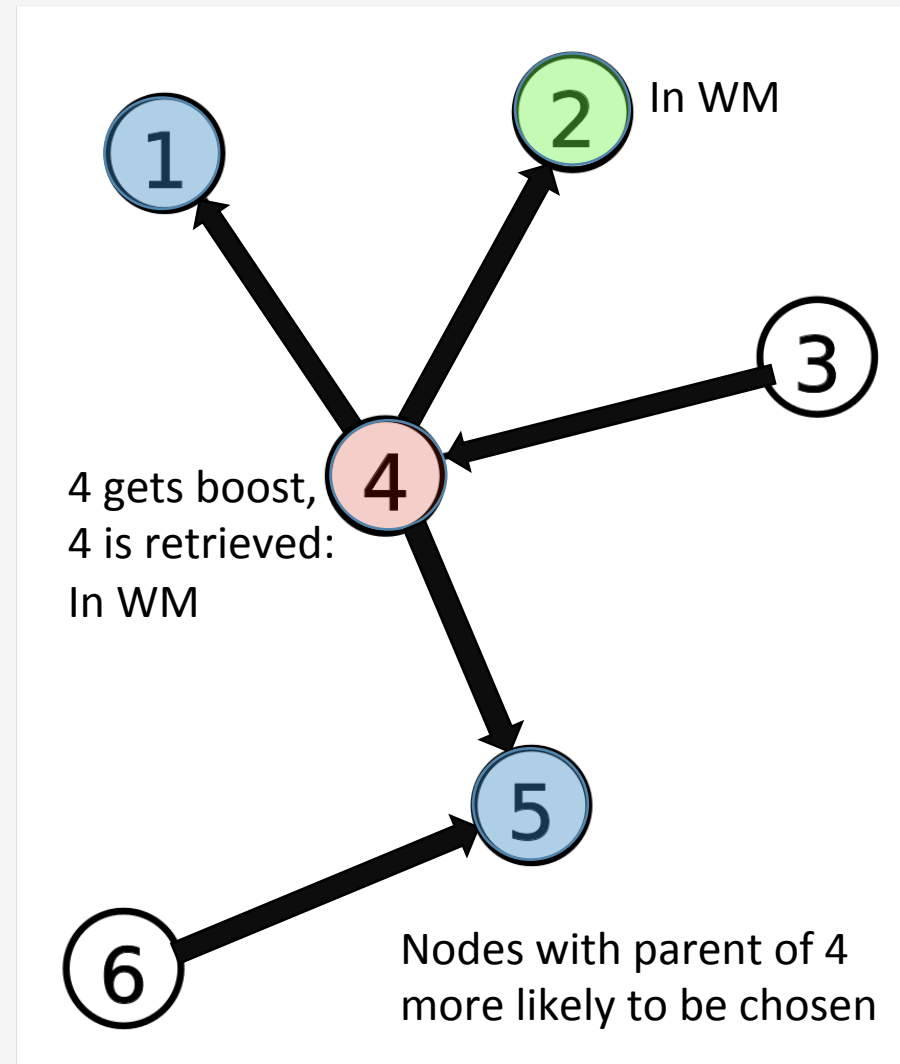
- Word-sense disambiguation
- Conversational topics

beneficial for query-based lookup to increase chances of correct retrieval

elements in working memory provide the “context”

possible nodes become weighted based on # of edges between themselves & WME's

the greater the number of relations between the node & the WME, the larger the probability of retrieval is



SemMemDB (FLAIRS-27 2014)

Created by:

- Yang Chen – University of Florida
- Milenko Petrovic & Micah Clark - Florida Institute for Human & Machine Cognition

Database implementation of semantic memory

Designed to exploit heuristically optimized query engines of RDBMS's for associative information retrieval

- Speed
- SQL
- Massive amounts of data

Semantic network stored as a table of symbolic triples:

Subject – Predicate (relation) – Object

SemMemDB - Retrieval

Retrieval in SemMemDB is based on ACT-R's base-level activation, with the addition of spreading.

- Non-probabilistic graph traversal

$$\text{RetrievalScore}_i = \underbrace{\ln(\sum_{k=1}^n t_k^{-d})}_{\text{Base-level Activation}} + \underbrace{\sum_{j \in Q} \text{weight}_{ij} * (S - \ln(1 + \text{degree}_j / \text{edges}_{ji}))}_{\text{Spreading Activation}}$$

Base-level Activation

Spreading Activation

i = subject node in dataset

n = number of presentations of node *i*

t_k = time since *k*th presentation of *i*

d = rate of activation decay

j = object node in dataset

Q is the contextual element source

S = constant parameter

edges_{ji} = relations between *j* and *i*

SemMemDB – Weak Points

paper contains efficiency testing only relating dataset size and query size to
does not provide time data on key elements of retrieval score calculation

- Connectivity of nodes
- History size

their implementation consists of a feed-forward spread

- Spreading from parent node to child node

did not implement materialized views – used tables/view hybrid instead

- Did not provide data on re-indexing time for dataset inserts
 - If not properly indexed calculation time will increase

does not incorporate hard constraints (only allows for look-up based on content
elements)

not integrated with cognitive architecture

SemMemDB – My Work

Currently have a working implementation of SemMemDB with Postgres

- Toy datasets return accurate spreads from queries of “context” nodes

Our implementation contains a feed-backward spread and materialized views

Future Work:

Comprehensive testing and analysis of timing

- Calculation
- Re-indexing/MV refresh

Drop Postgres as RDBMS and produce a standalone C++ implementation

- No need to connect to DB server/use interface drivers

Optimize algorithms to efficiently be able to retrieve resultant nodes in as little time as possible

Golden Nuggets and Coal



Our implementation is currently functional and does produce an accurate spread based on trials with toy datasets

We have a good path-to-goal for our research, and should achieve bigger and better in the coming weeks!



- No official empirical data!